

# BIOMETRIC SIGNATURE AUTHENTICATION WITH LOW-COST EMBEDDED STYLUS

Divas Subedi<sup>1</sup>, Digesh Chitrakar<sup>1</sup>, Isabella Yung<sup>1</sup>, Yicheng Zhu<sup>1</sup>,  
Yun-Hsuan Su<sup>2</sup>, Kevin Huang<sup>1</sup>

<sup>1</sup>Trinity College, Department of Engineering, 300 Summit St, Hartford, CT 06106

<sup>2</sup>Mount Holyoke College, Department of Computer Science, 50 College St, South Hadley, MA 01075

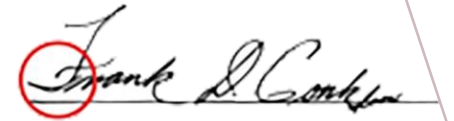
# MOTIVATION

- Current authentication methods
  - Passwords, MFA
- Signatures have been used as form of authentication
  - Used in ballots, checks, legally binding papers
- Current signature verification methods are not reliable
  - Extremely manual and expensive undertaking
  - Observed utility of their expertise over novices are not entirely confirmed
- Handwriting and signatures is unique to each individual person
- Non-invasive, user-friendly and can be readily integrated into current system

**BALLOT**



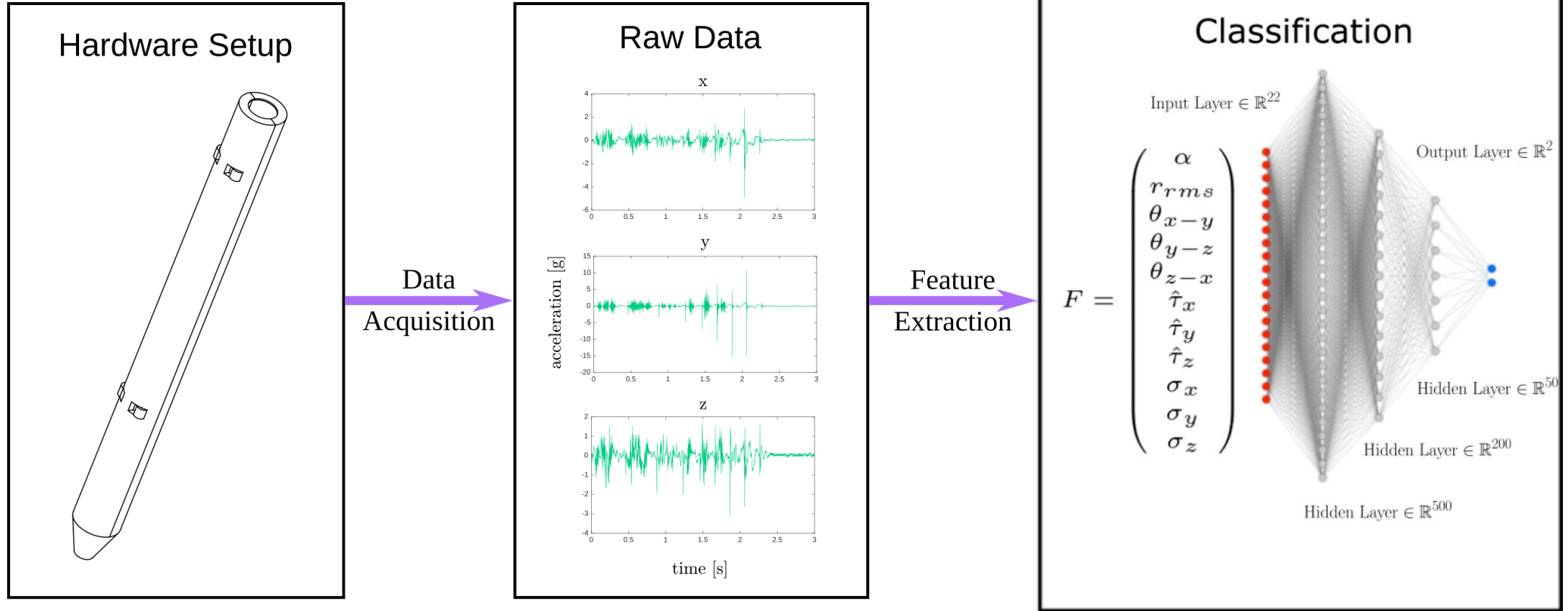
**VOTER FILE**



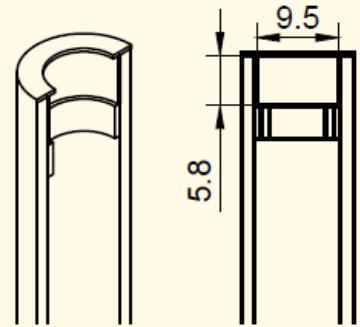
# RESEARCH GOALS

- Design and develop a low-cost pen that authenticates users via signature
- Propose a novel approach to use signature as biometric authentication
  - Observe how the signature was written rather than just the outcome
  - This iteration of the device is based on inertial measurements collected by two accelerometers
- Extract features based on collected data
- Train a model using the features that can authenticate a signature

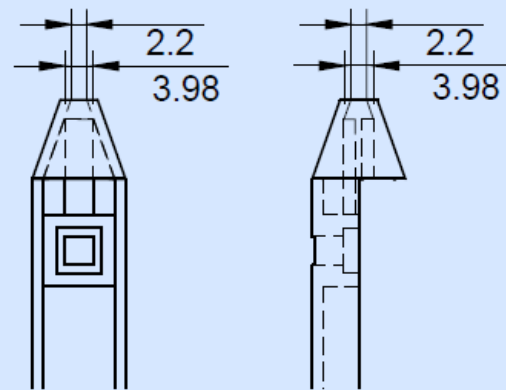
# WORKFLOW



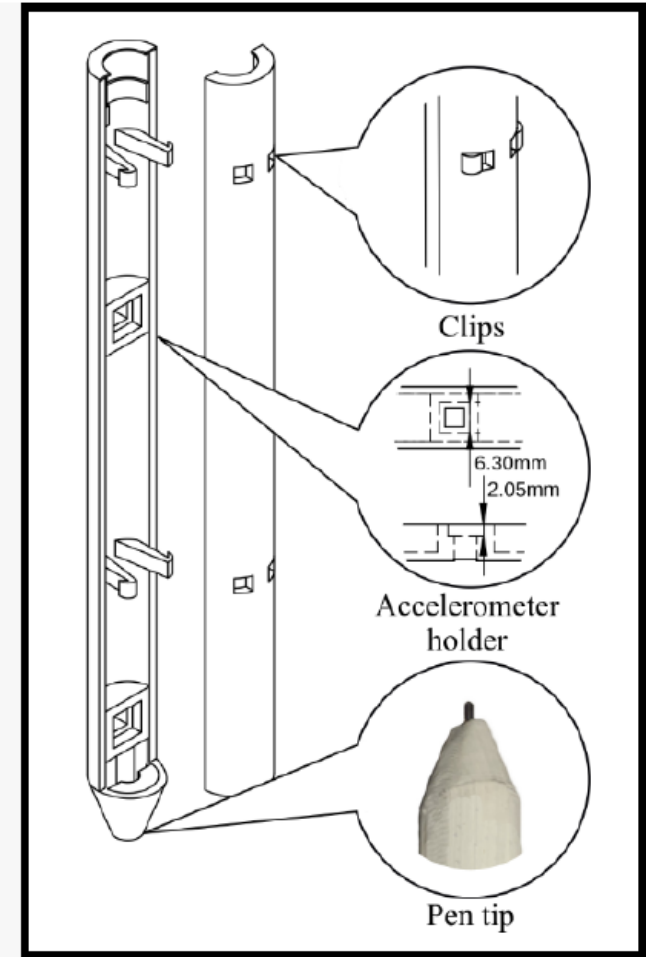
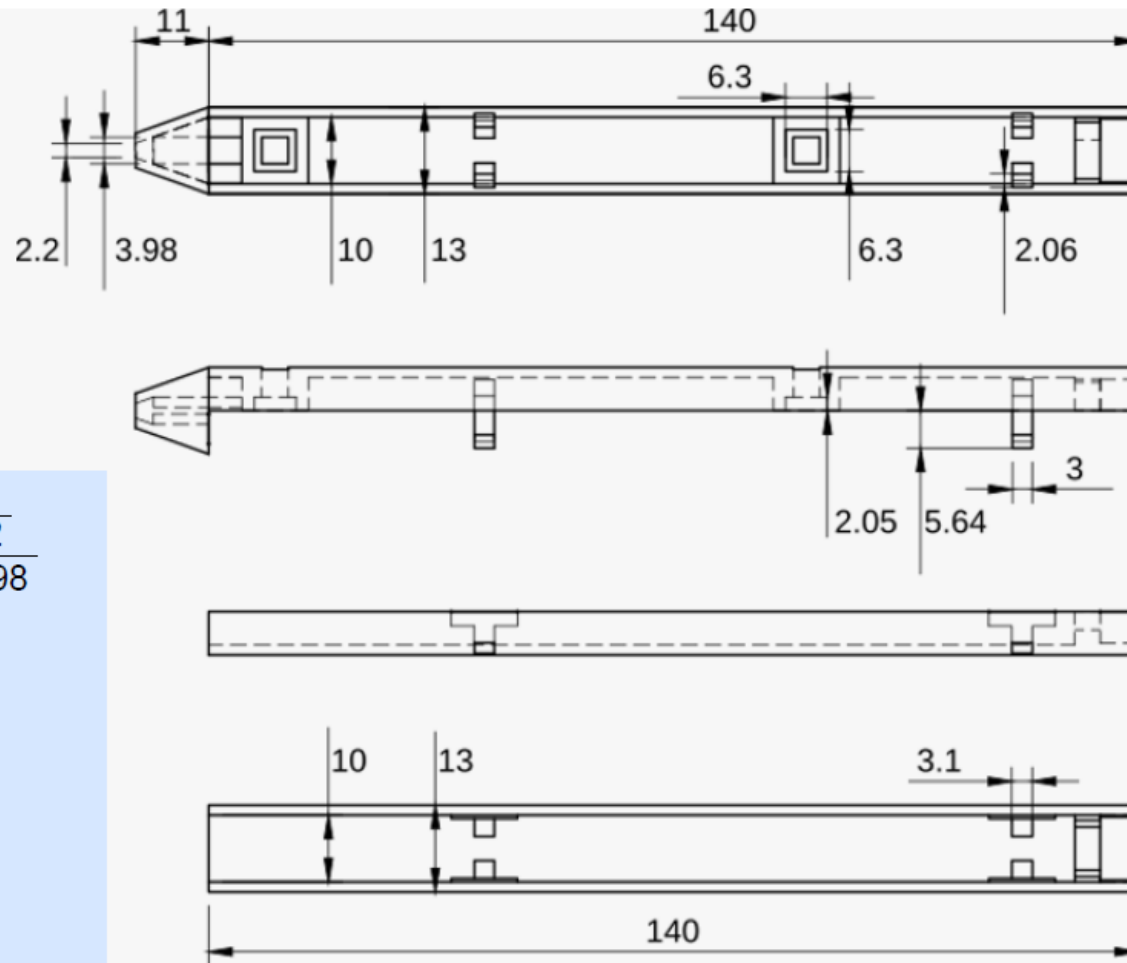
# STYLUS DESIGN

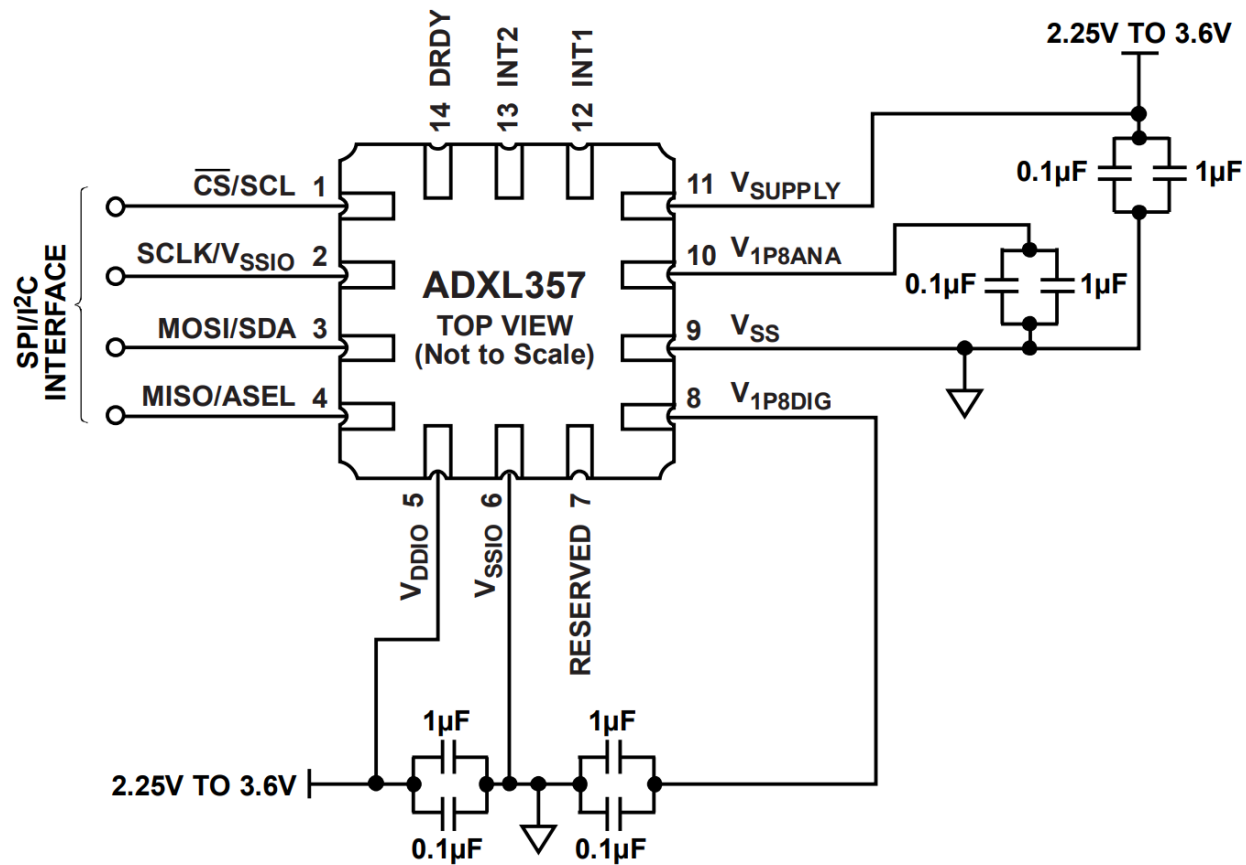


Pin Connector



Refill Holder



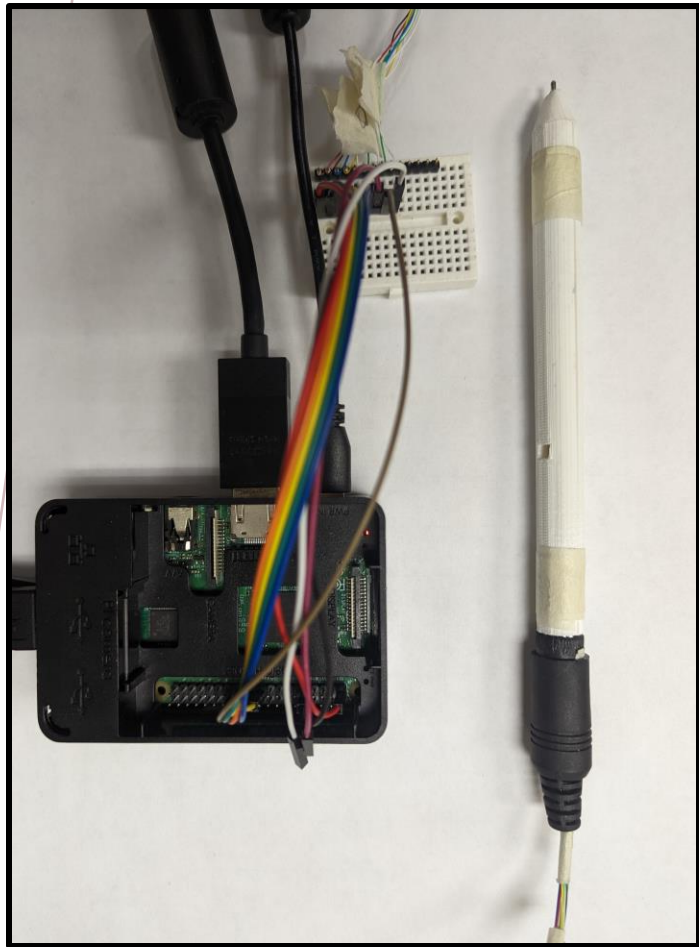


Circuit layout for one ADXL357

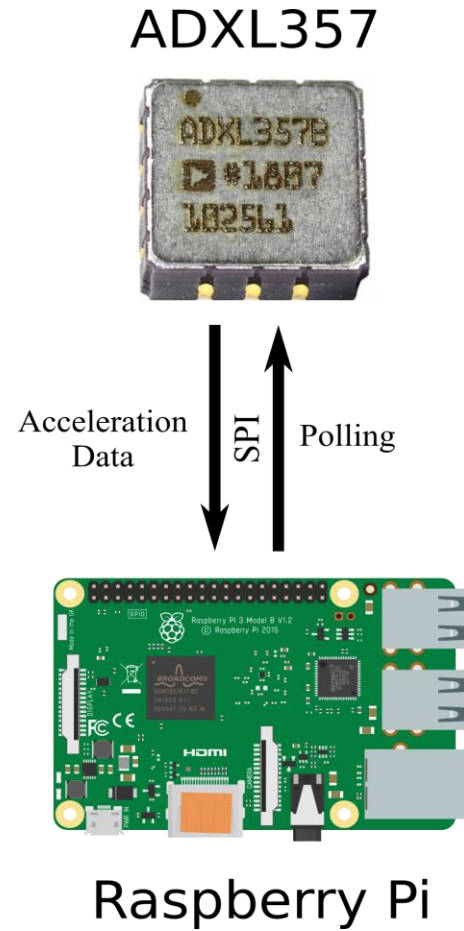
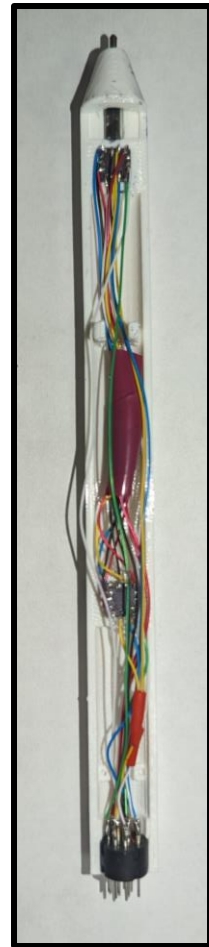
# ACCELEROMETER

## ADXL357

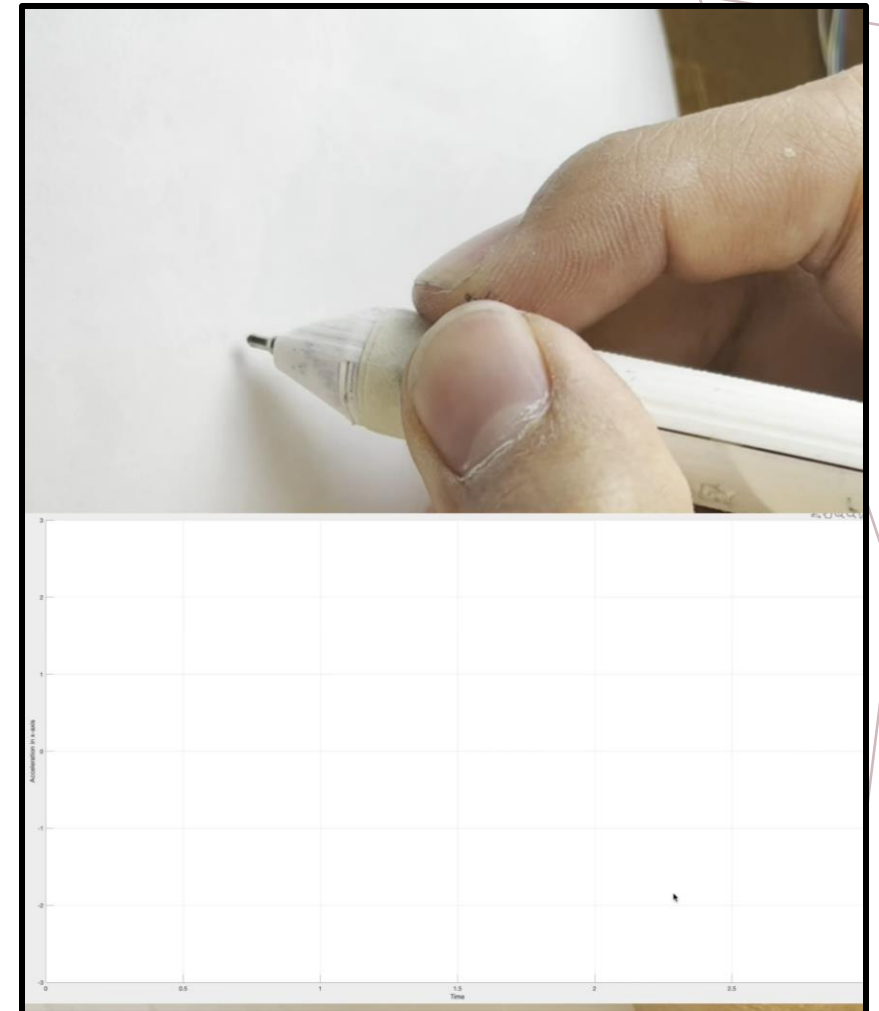
- 3 Axes measurement
- Bandwidth: 2 kHz
- Range: 20g
- Sensitivity:  $7.23 \times 10^{-4} \text{ g}$
- Serial Peripheral Interface (3.4 MHz)



Physical realization of the pen



Data Acquisition  
Process



Collection of acceleration data from signature

# DATA COLLECTION

Two separate users' signatures served as authentication targets: **Subject 0** and **Subject 1**

Two signature labels were collected:  
**Authentic** and **Forged**

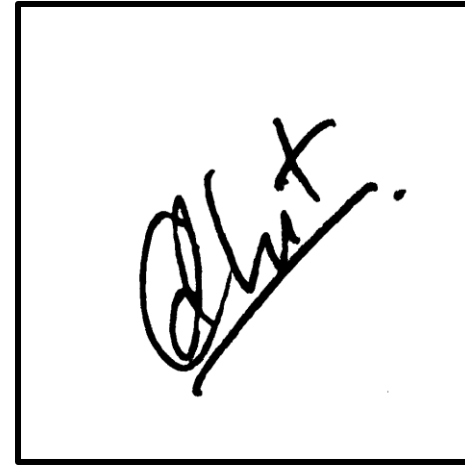
## Authentic Signature [2 Subjects]

- 212 signatures

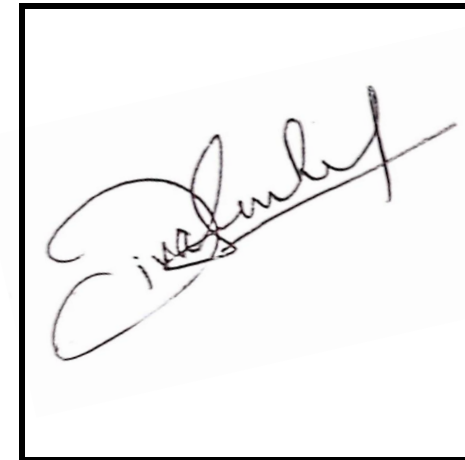
## Forged Signature [8 Subjects]:

- 30 forged signatures
- 15 random words/scribbles

Subject 0



Subject 1



Authentic

Forged



# DATA COLLECTION

The subjects were all right-handed and between the ages of 18 and 23 years old

A brief introduction to the forgery task included:

- an introduction to the embedded device
- a description of the time duration:
  - under 3 seconds for Subject 0
  - under 5 seconds for Subject 1
- for each signature class, a copy (to scale) of the authentic signature graphical output
- time for the forger to practice with the pen to forge the target signature (20 minutes or whenever satisfied)

Signature of Subject: 06  
Signature by Subject: 06

*dhrit.*

<i>dhrit.</i>	<i>dhrit.</i>	Defer
<i>dhrit.</i>	<i>dhrit.</i>	Fibre
<i>dhrit.</i>	<i>dhrit.</i>	Coat
<i>dhrit.</i>	<i>dhrit.</i>	Gond
<i>dhrit.</i>	<i>dhrit.</i>	Sperm
<i>dhrit.</i>	<i>dhrit.</i>	Gawze
<i>dhrit.</i>	<i>dhrit.</i>	Musky
<i>dhrit.</i>	<i>dhrit.</i>	Beryl
<i>dhrit.</i>	<i>dhrit.</i>	Snore
<i>dhrit.</i>	<i>dhrit.</i>	Prane
<i>dhrit.</i>	<i>dhrit.</i>	Rhine
<i>dhrit.</i>	<i>dhrit.</i>	Bothy
<i>dhrit.</i>	<i>dhrit.</i>	Clasp
<i>dhrit.</i>	<i>dhrit.</i>	Haily
<i>dhrit.</i>	<i>dhrit.</i>	Gloss

# DATA COLLECTION

For both Subject 0 and Subject 1 signatures, a database is collected that includes acceleration time series for:

1. 212 handwritten positive (authentic) signatures;
2. 343 handwritten negative (forged) signatures, consisting of:
  - 238 forged replicas of authentic signature;
  - 105 random words/scribbles.

Each type of signature thus includes a total of 555 collected samples as a dataset

# ORIENTATION NORMALIZATION



$$\mathbf{v} = -\frac{\hat{\mathbf{a}}_{\perp \mathbf{g}}}{\|\hat{\mathbf{a}}_{\perp \mathbf{g}}\|}$$

$$\mathbf{G} = \begin{bmatrix} \hat{\mathbf{a}} \cdot \mathbf{g} & -\|\hat{\mathbf{a}} \times \mathbf{g}\| & 0 \\ \|\hat{\mathbf{a}} \times \mathbf{g}\| & \hat{\mathbf{a}} \cdot \mathbf{g} & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{F} = \begin{bmatrix} \hat{\mathbf{a}} & \mathbf{v} & \mathbf{g} \times \hat{\mathbf{a}} \end{bmatrix}$$

$$\mathbf{U} = \mathbf{F} \cdot \mathbf{G} \cdot \mathbf{F}^{-1}$$

# FEATURES

$$\alpha = \arccos (\hat{\mathbf{a}} \cdot \mathbf{g})$$

$$r_{rms} = \sqrt{\frac{1}{N} \sum_t a_x^2(t) + a_y^2(t) + a_z^2(t)}$$

$$\theta_{i-j} = \arctan \left( \frac{a_{i_{rms}}}{a_{j_{rms}}} \right)$$

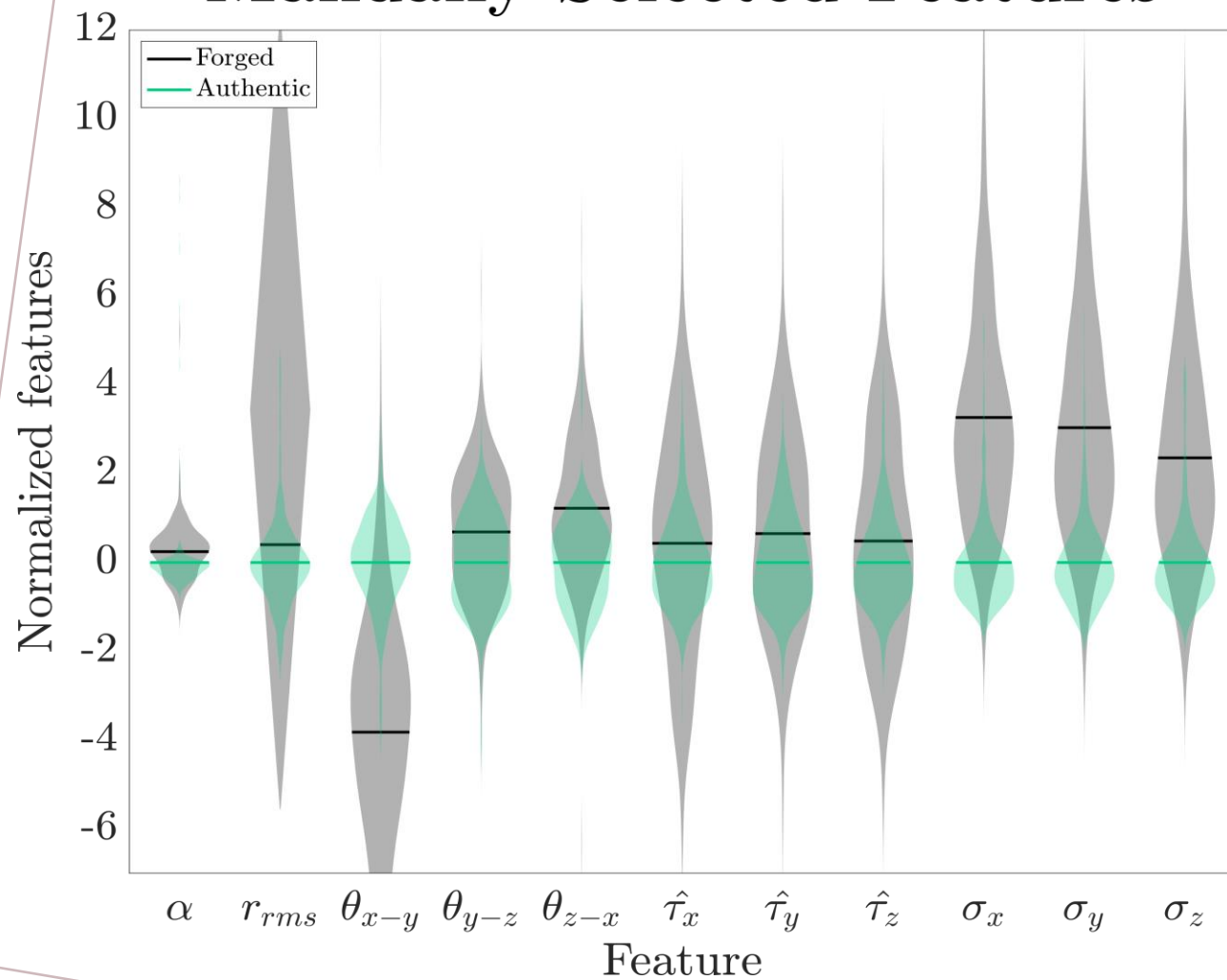
$$\hat{\tau}_i = \frac{1}{N_\tau} \sum_t E_i(t)t$$

$$\sigma_i = \frac{1}{N_\tau} \sum_t E_i(t)t^2 - \hat{\tau}_i$$

$$N_\tau = \sum_t E_i(t)$$

$$E_i(t) = a_i^2(t)$$

# Manually Selected Features



$\alpha$  : Angle between gravity and tilt of pen

$r_{rms}$  : Measure of energy put into signature

$\theta_{i-j}$  : Ratio of energy distribution on axes i & j

$\hat{\tau}_i$  : Metric of temporal distribution of energy (Mean)

$\sigma_i$  : Metric of temporal distribution of energy (Std)

# CLASSIFICATION

A Multilayer Perceptron Neural Network was trained with manually selected features

**Input:** 22 manually crafted features in **F**

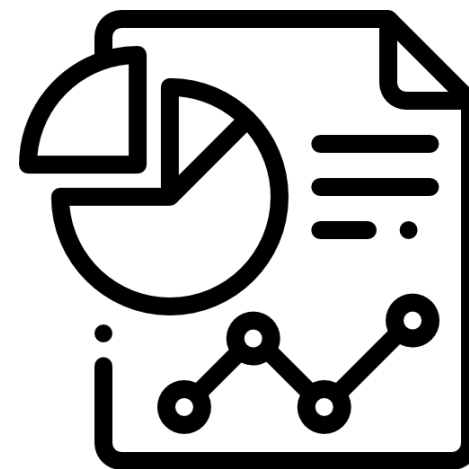
**Structure:** Three hidden layer with 500, 200, and 50 perceptrons in each layer respectively

**Optimization:** This model optimized the log-loss function using Limited-memory Broyden–Fletcher–Goldfarb–Shanno (LBFGS)

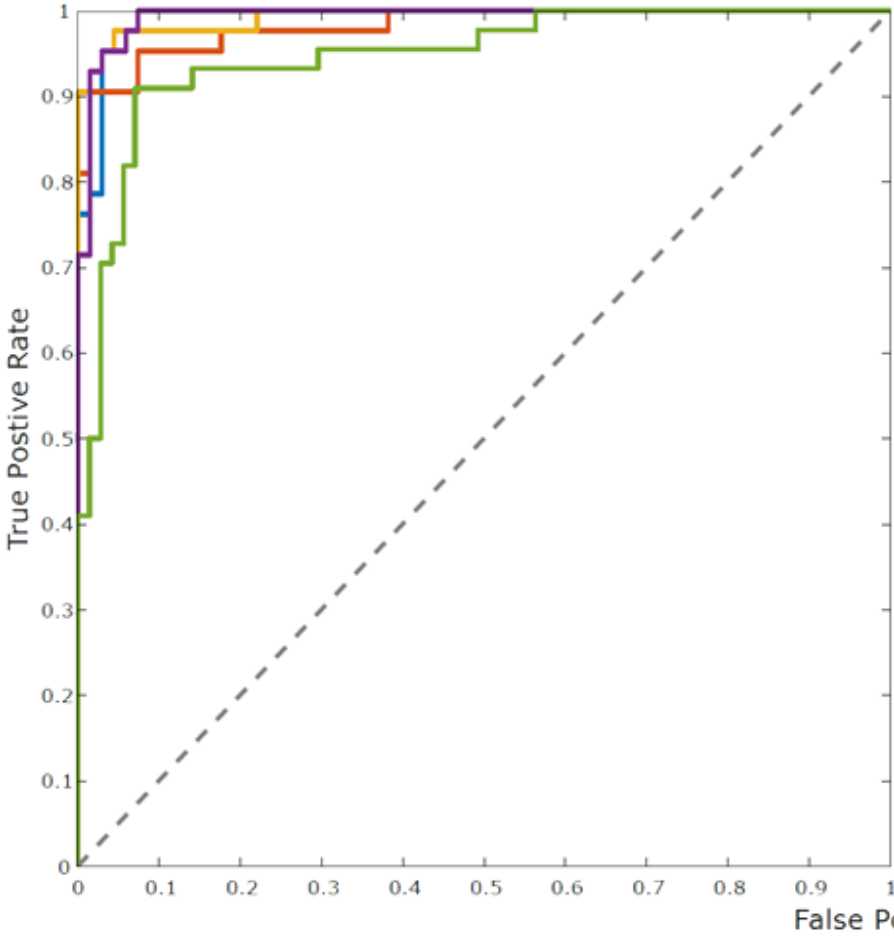
**Training:** An 80-20 split was heuristically determined

Each dataset was split into 5 distinct folds with uniform distribution of authentic and forged signatures

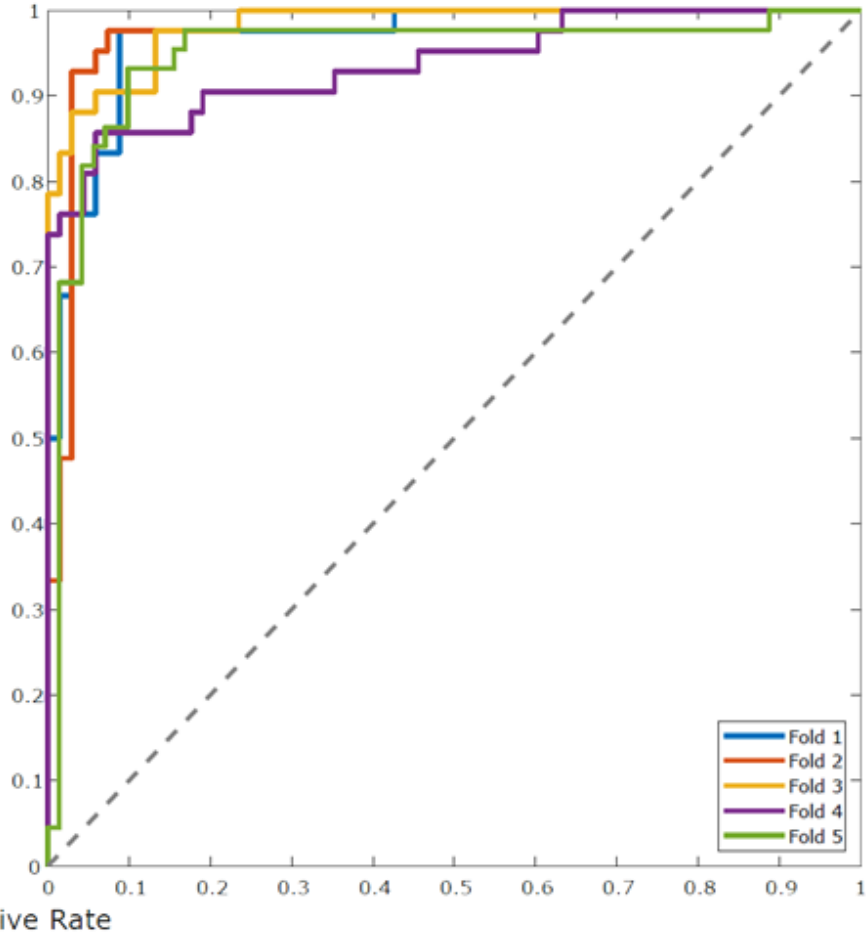
# RESULTS



# Receiver Operating Characteristic



Subject 0



Subject 1

## AUC

Fold	Subject 0	Subject 1
1	0.9919	0.9678
2	0.9818	0.9758
3	0.9926	0.9814
4	0.9930	0.9373
5	0.9465	0.9481



		Target Class	
		0	1
Predicted Class	0	True Negatives 328 59.1%	False Negatives 21 3.8%
	1	False Positives 15 2.7%	True Positives 191 34.4%
Subject 0		Precision: 92.7% (7.3%) Recall: 90.1% (9.9%) NPV: 93.9% (6.1%) Specificity: 95.6% (4.4%) Accuracy: 93.5% (6.5%)	

		Target Class	
		0	1
Predicted Class	0	True Negatives 323 58.2%	False Negatives 19 3.4%
	1	False Positives 20 3.6%	True Positives 193 34.8%
Subject 1		Precision: 90.6% (9.4%) Recall: 91.0% (9.0%) NPV: 94.4% (5.6%) Specificity: 94.2% (5.8%) Accuracy: 93.0% (7.0%)	

# FUTURE WORKS

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Addition of more sensors like pressure sensor and gyrometer

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Exploration of other feature extraction and training techniques

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Explore on possibility of text transcription with this device

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Expanding the study to have more signature as authentication target

# THANK YOU

Thank you for your attention. The authors would like to thank the AIM 2023 organizing committee and welcome all questions via email at [kevin.huang@trincoll.edu](mailto:kevin.huang@trincoll.edu)

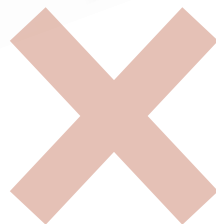


This work was done as an extension to the Senior Engineering Capstone Project 2022. We would like to acknowledge Trinity College and Travelers Insurance for funding the project and making this research possible. We would also like to thank Dr Clayton Buyers for his support.

# QUESTIONS



Adhnt.



Adhnt.



Adhnt.



Adhnt.



# FEATURE DIFFERENCE BETWEEN SQUARES AND CIRCLES

